TaRad: A Thing-centric Sensing System for Detecting Activities of Daily Living

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Abstract. Activities of Daily Living Scale (ADLs) is widely used to evaluate living abilities of the patients and the elderly. Most of the currently proposed approaches for tracking indicators of ADLs are human-centric. Considering the privacy concerns of the human-centric approaches, a new thing-centric sensing system, named TaRad, for detecting some indicators of ADLs (i.e. using fridge, making a phone call), through identifying vibration of objects when a person interacts with objects. It consists of action transceivers (named ViNode), smart phones and a server. By taking into account the limited computation resource of the action transceiver, and the drift and accuracy issues of the cheap sensor, a method of extracting features from the vibration signal, named ViFE, along with a light-weight activity recognition method, named ViAR, have been implemented in ViNode. Besides, an operator recognition method, named ViOR, has been proposed to recognize the acting person who generates vibration of action transceiver, when two or more people exist simultaneously within an area. Experimental results verify the performance of TaRad with different persons, in terms of the sensitivity to correctly detect the activities, and probability to successfully recognize the operators of the activities.

Keywords: Activities of Daily Living · Thing-Centric Sensing · Action Transceiver · Activity Detection · Operator Recognition.

1 Introduction

Aging population has become one of the main concerns in both developed countries and developing countries, according to a report from World Health Organization (WHO) [1]. People may suffer with a higher probability from many kinds of diseases when getting older. Activities of Daily Living Scale (ADLs) [2] is widely used to evaluate living abilities of the patients and the elderly, especially for those who need to be under medical control. There are many indicators of ADLs, such as leaving house, using toilet, taking a shower, going to bed, preparing dinner, using fridge, making a phone call, getting drink and so on.

Traditionally, these indicators were usually evaluated by professional institutions via asking the involved people to fill questionnaire periodically, or requiring them to record their own activities manually and then collecting the recorded data into electronic forms. This method is not only inaccurate, but also obtrusive to the elderly or the patient's living. With rapid development of sensing technology, both wearable sensors (e.g. Radio frequency identification (RFID) sensors [3], body sensor networks [4, 5], accelerometer in smart watch [6] and wrist-worn sensors [7]) and fixed sensing infrastructure (e.g. Passive InfraRed (PIR) sensors [8], camera [9], radio tomography networks [10], WiFi network [11–13], light sensing [14, 15]) have been exploited to track indicators of ADLs. Although these approaches make the ADLs assessment more objective and mitigate obtrusiveness for the assessed people, they are based on rich information about people's lives and biometrics (i.e. ***human-centric***[16]), which raise some severe privacy concerns [17].

Considering the privacy concerns, some researchers proposed to take contact switches [18], binary sensors [19], RFID [20] to detect object usage, and infer human activities using such kind of environmental information on things. In [21], the authors record electricity consumed by room lights and various appliances and then translate it into the probability of a particular ADL. We call them ***thing-centric*** activity recognition. Because vibration is a commonly occurring phenomenon when a person poses an activity on an object, some researchers have exploring activity recognition through vibration sensors [22]. However, there are still two main problems existing to be addressed. (i) Resource limitation problem, which means how to design activity recognition algorithm, so that it can perform high recognition accuracy, against the limited computation resource of the action transceiver, and the drift and accuracy issues of the cheap sensor. (ii) Multiple-people interference problem, which means how to recognize the acting person who generates vibration of action transceiver, when there are two or more people exist simultaneously within an area.

In this paper, we propose a new thing-centric sensing system, named TaRad, which consists of action transceivers, smart phones and a server, for detecting some indicators of ADLs, through identifying vibration of objects when a person interacts with objects. Through solving these two problems, we make the following contributions:

(i) A method of extracting features from the vibration signal, named ViFE, along with a light-weight activity recognition method, named ViAR, have been implemented in resource limited action transceivers, named ViNode, in TaRad. Considering the limited computation resource of the sensor nodes, we only need to detect whether the object is moved or not through processing vibration signal, but not to analyze different vibration patterns of different actions posed on the objects, such as tap and swipe on object surface [23].

(ii) An operator recognition method, named ViOR, has been proposed to solve the multiple-people interference problem, by exploiting the potentially d-

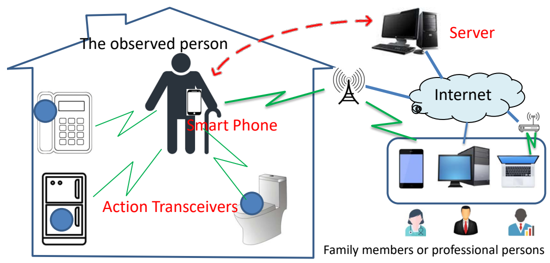

Fig. 1. System architecture of TaRad.

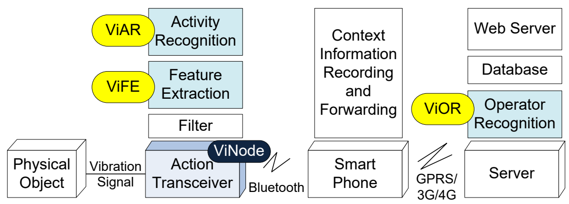

Fig. 2. Hardware and software modules comprising the TaRad system.

ifferent RSSI values between the action transceiver and the smart phone when different persons conduct a same activity. To the best of our knowledge, the multiple-people interference problem has not been solved in the existing thing-centric sensing systems.

(iii) The system has been implemented to detect two kinds of activities, which are making a phone call and using fridge, and evaluated with real experimental tests. Results verify the performance of TaRad with different persons, in terms of the sensitivity to correctly detect the activities, and probability to successfully recognize the operators of the activities.

The rest of the paper is organized as follows. Section 2 gives an overview of our proposed thing-centric sensing system for tracking indictors of ADLs. Section 3 elaborates the algorithms and implementation of ViNode, ViFE, ViAR and ViOR. Section 4 presents the evaluation experiments and results. Section 5 makes a conclusion.

2 System Design

The system architecture of TaRad, which is a thing-centric sensing approach for detecting activities of daily living, is shown in Fig. 1. It mainly consists of three key components, including action transceiver, smart phone and server. The action transceiver is an embedded device, which is attached on a certain home facility like phone and fridge, for sensing the vibration of the attached object, and recognizing the activity exerted on the object.

The action transceiver is composed of a motion sensor and a micro processor, for collecting vibration data and doing data processing on the site for activity recognition. It sends the results of activity recognition (including the identity of the used object) through Bluetooth broadcast to the smart phone. When this receives a message of recognition result, it records the context information, e.g. the Received Signal Strength Indicator (RSSI), and then forwards these information to the server through Internet. **By having the smart phone just measuring context (RSSI) we avoid the privacy invasiveness of human-centric approaches.** The server determines the corresponding operator of the activity based on the received message and the associated RSSI information, and stores the determined results in database, from where they can be retrieved by enabled caregivers and professionals.

The main software modules running in each hardware component are shown in Fig. 2. For the action transceiver (i.e. ViNode), it mainly includes three modules, which are for signal preprocessing (i.e. filter), feature extraction (i.e. ViFE), and activity recognition (i.e. ViAR). For the smart phone, it mainly includes a module to record context information of the recognized activity as described above, and forward it to the server. For the server, it mainly includes three modules, which are for operator recognition (i.e. ViOR), data storage (i.e. database) and providing web service (i.e. web server). Due to space limitation, we will present the implementation of the most challenging hardware component and software modules in TaRad, which are the ViNode, ViFE, ViAR, and ViOR, in the following sections.

3 System Implementation

3.1 Action transceiver (ViNode)

To make a feasible thing-centric passive sensing system for detecting activities of daily living, the action transceiver has to be small in dimension and low in cost, while maintaining a long battery life. We have chosen the chipset CC2540 and the accelerometer LIS3DH to compose the action transceiver (ViNode) for their suitable characteristics. As shown in Fig. 6, the ViNode size (40 mm by 40 mm) makes it small enough to be fixed on the surface of physical objects, as a fridge door and a telephone handset.

The chipset CC2540 integrates a *low power Bluetooth* (IEEE 802.15.1) compliant radio transceiver and an 8KB SRAM. The CC2540 chip is set in the ***broadcast mode***, i.e. no long-lasting connection is required between pairs of devices. This allows multiple action transceivers to advertise their information to listening smart phones in a limited area in a scalable way. Because CC2540 S-RAM and computational capability are limited, it is required that the algorithms running on it should be light-weight. These algorithms, particularly ViFE and ViAR, are elaborated as follows.

3.2 Feature Extraction (ViFE)

As shown in Fig. 2, when the physical objects are moved by the observed person, the accelerometer in the action transceiver will generate some signals. The

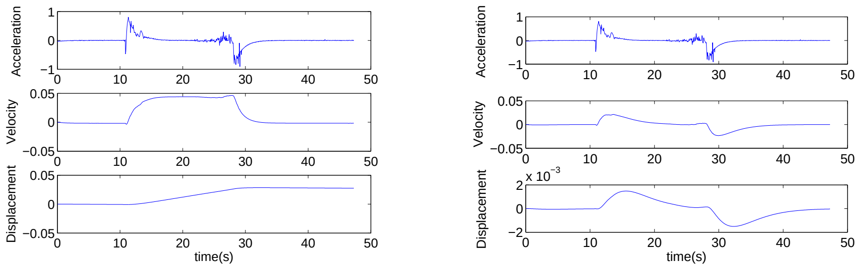

Fig. 3. Comparison of the results of integral of the acceleration (a) before using ViFE and (b) after using ViFE.

original acceleration signals include (i) acceleration signal caused by motion of the object, (ii) acceleration signal of gravity, (iii) noise generated by jitter, (iv) random drift signal caused by accelerometer. Because the signal components (ii) and (iii) both have a lower frequency, they can be removed by a high-pass filter. Because the high-pass filter is widely used in the signal processing, we save some space by omitting the detail of the filter. Here, we elaborate more on the feature extraction module.

Compared with other features in frequency domain, *vibration* and *movement distance* are easier to be recognized (leading to a lower-complexity algorithm), therefore they are chosen as classification features for detecting some indicators of ADLs (i.e. using fridge, making a phone call). The acceleration signal generated by the accelerometer of ViNode can be directly taken as the feature of vibration. As for the feature of movement distance, it can be calculated by using a secondary integral of the acceleration data. In particular, denoting the acceleration at time t as a_t, velocity at time t as v_t, we have the velocity $v_{t'}$, where $t' = t + \Delta t$:

$$v_{t'} = v_t + a_t \Delta t. \tag{1}$$

Accordingly, denoting the displacement at time t as d_t, we can get the displacement at time t':

$$d_{t'} = d_t + v_t \Delta t. \tag{2}$$

We refer to these two equations as velocity formula and displacement formula respectively. Using the data of making a phone call as an example, the calculated velocity and distance result is showed in Fig. 3(a). From the figure, we can see that the acceleration data has a positive pulse at 11s, when the velocity and the displacement start increasing. After 2 to 3 seconds, the handset of the telephone is lifted, therefore the acceleration decreases to zero, while the velocity remains unchanged. However, as the velocity is larger than 0 after 14 seconds, the displacement keeps increasing. The result is against common sense, because the displacement should be unchanged rather than increasing after the handset is lifted. The reason why the displacement keeps increasing is that the acceleration data also reflects the rotation of the handset. Furthermore, as the displacement does not go back to 0 when the phone is hung up. Hence, we correct the velocity formula and the displacement formula as follows.

$$v_{t'} = kv_t + a_t \Delta t \tag{3}$$

$$d_{t'} = kd_t + v_t \Delta t \tag{4}$$

k is a coefficient, which ranges between 0 and 1, and is multiplied with the current velocity v_t or displacement d_t when calculating the corresponding value at time t' ($t' = t + \Delta t$). It is worth noting that k is correlated with the sampling frequency, as it realizes the integration operation similar with the low-pass filter.

The calculation of velocity and displacement formulated by equation (3) and (4) comprises the significant step of feature extraction, which is called ViFE. The calculated velocity and displacement after using ViFE is shown in Fig. 3(b). From the figure, we can see that when the handset is lifted or putted down, the velocity and displacement signal both rise to a certain level and then resume to 0 after a time period of about 20 seconds. This result demonstrates the possibility of detecting the activity (i.e. making a phone call) by setting a threshold on the displacement calculated with ViFE. It can also be applied in calculating the dragging distance of a fridge door and be effective in detecting the activity of using fridge. Next, we will describe the algorithm of detecting activity based on the result of ViFE.

3.3 Activity Recognition (ViAR)

Considering the limited computational capacity of the action transceiver (ViNode), as presented in section 3.1, we design an activity recognition algorithm based on decision tree, which is called ViAR. A decision tree has a flowchart-like structure, in which each non-leaf node represents a "test" on an attribute while each branch represents the outcome of the test and each leaf node represents a class label. The paths from root to leaves represent classification rules.

The main process of ViAR is depicted by Fig. 4, which roots from the acceleration and has a branch in displacement. The results of decision tree are represented by the two class labels at the leaves, which are "object is used" and "object is not used". The challenge of constructing the decision tree is how to properly set the two thresholds, namely $\mathrm{T_{acc}}$ and $\mathrm{T_{dis}}$. We firstly set initial values, $\mathrm{T_{acc}} = t_a$ and $\mathrm{T_{dis}} = t_d$, for these two thresholds, and then adjust them by a training process. The training data is expressed as a triad $(acc, dis, stat)$, where acc means the acceleration, dis means the displacement, and $stat$ means the labeled class of object usage. For each triad in the training set, when the classified status s equals to $stat$, the thresholds don't need to be adjusted. Otherwise, the thresholds need to be adjusted as formulated by the following equations.

$$\mathrm{T_{acc}} = acc + (acc - \mathrm{T_{acc}}/2) \tag{5}$$

$$\mathrm{T_{dis}} = dis + (dis - \mathrm{T_{dis}}/2) \tag{6}$$

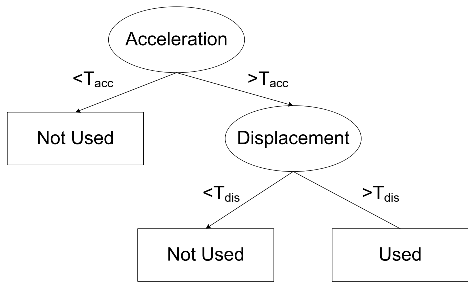

Fig. 4. The decision tree of ViAR.

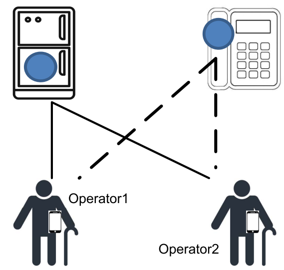

Fig. 5. Illustration of a scenario causing the multiple-people interference problem.

3.4 Operator Recognition (ViOR)

Since it is highly probable that there are more than one observed persons coexist in the same area, a broadcast of the recognized activity by an action transceiver will be received by multiple smart phones carried by them. As illustrated in Fig. 5, two operators live in the same room, where the operator1 makes a phone call while the operator2 uses the fridge. However, both of the smart phones carried by the operators will forward the received results of action detection to the server, which will cause mixed decision of who is generating the activity. Therefore, we design an operator recognition method, named ViOR, in TaRad.

As mentioned in section 2, when the smart phone receives a message of recognition result, it forwards the message along with the RSSI recorded when it receives the message. Firstly, we build models for each person operating on an object. For example, $M(opr, obj)$ denotes the model of operator opr on object obj. Considering the instability of Bluetooth signal, to ensure the integrity of the RSSI data, the ARQ (Automatic Retransmission Request) mechanism and a time window strategy are used to preprocess the data before building the model. The size of time window n can be calculated by using the equation $\mathrm{P} = 1 - (1 - \mathrm{PRR})^n$, if we know the packet reception ratio (PRR) of the link between the action transceiver and the smart phone, and specify the probability (P) of successfully receiving at least one RSSI message in the time window.

We denote the RSSI data for model training as $T = \{D_i\}, i \in [0, t]$, $D_i = \{d_i^j\}, j \in [0, v]$, d_i^j represents every valid RSSI value in the i^{th} time window, and v is the number of valid data in the i^{th} time window, t is the number of time windows for training. The model established based on the training data is expressed as $M(opr, obj) = \{m_i\}, i \in [0, t]$, where

$$m_i = \frac{\Sigma_{j=0}^{v} d_i^j}{v}. \tag{7}$$

Then, when the server receives a set of messages about a recognized activity, denoted as (opr, obj, R), where $R = \{r_i\}$, r_i is the carried RSSI value with each message, it uses interpolation method to do curve fitting based on $M(opr, obj)$ to

Parameter	Value
Sampling frequency of the accelerometer (Hz)	25
Cut-off frequency (Hz)	0.5
Coefficient k in ViFE	0.98
Initial value of $\mathrm{T}_{\mathrm{acc}}$ in ViAR	0.4
Initial value of $\mathrm{T}_{\mathrm{dis}}$ in ViAR	1.2×10^{-3}
The size of time window n in ViOR	2
T_{δ} of ViOR	0.05

Fig. 6. Demonstration of the experimental scenarios and the parameter settings.

judge whether *opr* is the operator of the object *obj*. In particular, ViOR computes the similarity between M and R based on the Euclidean distance equation, as shown in equation (8). If $\delta(M, R)$ is less than a threshold T_{δ}, *opr* is judged as the operator of the object *obj*.

$$\delta(M, R) = \sqrt{\sum_{i=0}^{t} (m_i - r_i)^2} \tag{8}$$

4 Experimental Evaluation

4.1 System Setups

The system has been implemented to detect two kinds of activities, which are making a phone call and using fridge. We have done some experiments on the system. The experimental scenario is shown in Fig. 6, from which we can see that ViNode is fixed on the handset of a telephone or the door of a fridge, and a smart phone is carried by each observed person. The parameter settings of the experiments are shown in Fig. 6.

4.2 Evaluation Metrics

The metrics, namely true positive (TP), true negative (TN), false positive (FP) and false negative (FN), are commonly used in a classification problem. In our experiments, positive instance means an activity is carried out, while negative instance means no activity is carried out. We take positive instances as the ground truth, and adopt the two metrics defined in equation (9) to evaluate the performance of TaRad. The metric named recall rate (R) is adopted to evaluate the sensitivity to correctly detect the indicators of ADLs (i.e. using

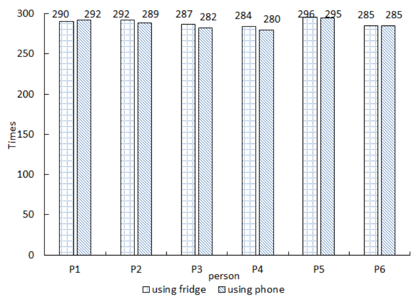

Fig. 7. True positive (TP) times of recognizing two activities for the 6 persons in our experiments, where each person take 300 times of each activity.

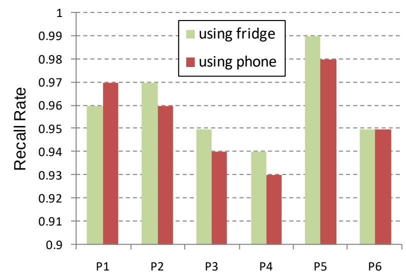

Fig. 8. Recall rate of recognizing two activities for the 6 persons in our experiments, where each person take 300 times of each activity.

fridge, making a phone call). The metric named accuracy (Acc) is adopted to evaluate the probability to successfully recognize the operators of the activities.

$$R = \frac{TP}{TP + FN}, Acc = \frac{TP + TN}{TP + TN + FP + FN}. \tag{9}$$

4.3 Evaluation Results of ViFE and ViAR

We recruited 6 persons as volunteers of our experiments. For each person, we asked him to intermittently conduct the activities, namely making a phone call and using fridge, for 300 times respectively. Fig. 7 shows the true positive (TP) times of recognizing the activity for each person in our experiments.

The recall rate of recognizing these two activities with ViFE and ViAR is shown in Fig. 8. We can see that the recall rates of recognizing the activity of using fridge for the 6 persons vary from 94% to 99%, which is 96% on average. For the activity of using phone, the recall rates vary from 93% to 98%, which is 95% on average.

From Fig. 8, we can also find that the recall rates of recognizing the activity of using phone for the 6 persons are little lower than those of recognizing the activity of using fridge, which is mainly caused by unintended touch of the handset of telephone during the experiments. In other words, the handset of telephone may be moved without making phone calls, which may cause the ViNode to make a mistaken judgement of the activity, so that it leads to a time of false positive classification.

4.4 Evaluation Results of ViOR

To evaluate the performance of ViOR in recognizing the operator, we firstly asked each of the volunteers to conduct the activity of using fridge for 40 times solely. The RSSI data in the messages sent from the ViNode on the surface of the fridge

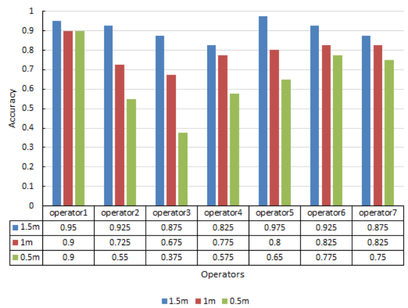

Fig. 9. Recognition accuracy of ViOR with different distances between the operator and the interferer.

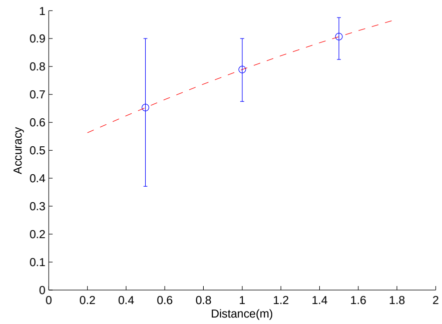

Fig. 10. The averages and different variation ranges of accuracy for different distances between the operator and the interferer.

to the smartphone carried by each operator were collected in these experiments for training the model $M(opr, obj)$, as presented in section 3.4. Then, we collected RSSI data in situations with two persons as a group. When one person conducted the activity, the other person was asked to walk around him as an interferer. In this part, we added one person to take part in the experiments, so totally 7 volunteers were recruited. We test the performance of ViOR in cases with different distances between the operator and the interferer, which are 1.5 meters, 1 meter, and 0.5 meter. In each case, the operator conducted the activity of using fridge for 40 times. The recognition accuracy of ViOR with different distances between the operator and the interferer is shown in Fig. 9. The results listed at the bottom of Fig. 9 show that when the distance between the operator and the interferer gets smaller, the accuracy of recognizing the operator gets lower. Fig. 10 shows the average accuracy of recognizing operator over the 7 persons in the three situations with different distances between the operator and the interferer. Generally speaking, ViOR can get an accuracy of 90.7 % on average at a distance of 1.5 meters, an average accuracy of 78.9% at a distance of 1 meter and an average accuracy of 65.3% at a distance of 0.5 meter. From Fig. 9, we can also see that in the situation that the distance is 1.5 meters, the accuracy of recognizing the operator for different persons varies from 0.825 to 0.975. However, in the situation that the distance is 0.5 meter, the accuracy varies from 0.375 to 0.9. Fig. 10 also shows the different variation ranges of accuracy for different distances between the operator and the interferer through the error bars.

The reduced performance of ViOR when the distance between the operator and the interferer gets smaller is mainly due to the following reason. It is probable that the operator and the interferer have a similar habit when they use the fridge, like keeping a similar distance from the fridge, which would build a similar model $M(opr, obj)$ for them. When the operator and the interferer keep a distance about 1.5 meters, the RSSI values are indistinguishable enough to make the similar models still work. However, when they get close, the RSSI values are indistinguishable, so that the models constructed by ViOR are unserviceable.

5 Conclusion

In this paper, a thing-centric human activity sensing system named TaRad has been proposed for passively tracking some indicators of ADLs. It consists of action transceivers (ViNode), smart phones and a server. By taking into account the limited computation resource of the action transceiver, and the drift and accuracy issues of the cheap sensor, a method of extracting features from the vibration signal, named ViFE, along with a light-weight activity recognition method, named ViAR, have been implemented in ViNode. Besides, an operator recognition method, named ViOR, has been proposed to recognize the acting person who generates vibration of action transceiver, when there are two or more people exist simultaneously within an area. Experimental results show the recall rates of recognizing the activities of using fridge and making phone call for 6 persons are up to 96% and 95% respectively on average. The accuracy of recognizing the right operator ranges from 90.7% to 65.3% on average when the operator and the interferer are apart from 1.5 meters to 0.5 meter. ViOR is not so efficient in recognizing operators in situations where coexisting persons have similar habits when conducting the same activity. We will improve the accuracy of ViOR by seeking a better method to construct more precise models for distinguishing operators in our future work.

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